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Optimization of Outside Unevenness and Substance Elimination Pace in Milling Zirconia Ceramic Material using Taguchi Technique and Regression Analysis

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Abstract

New materials are being developed as the need arises which creates interest to the researchers to identify the optimum combination of parameters during machining. In this paper, an experimental investigation was conducted for dry milling of zirconia ceramic material using Taguchi technique and Regression Analysis. Cutting momentum, feed rate, and intensity of cut were chosen as key parameters of the function of optimization by making effective combination of machine limit during machining. ANOVA was the process which was used to determine the effects of parameter on outside unevenness and substance elimination pace. The foremost essential factor responsible for outside unevenness was the cutting momentum whereas for substance elimination pace cutting momentum and intensity of cut were the responsible factors. To ascertain the best possible parameters Taguchi and Linear regression equation was used. Confirmatory test affirm that the actual values were very close to the predicted values. Minitab 17 software was utilized for analysis and optimisation.

Keywords: zirconia ceramic, taguchi, regression, optimization, outside unevenness, substance elimination pace.

1. INTRODUCTION

Zirconia ceramic is a material which has incredibly first-class chemical, mechanical, and thermal property. Due to which it finds multiplicity of approaches in dental, orthopaedic, aerospace, tool and an assortment of other industries. It is tough to dig up the access of chips that are formed after machining as the chips formed are in powder form. The on the whole widespread and extensively process applied to separate metal from substances in industries is milling. Then as legislation central feature that determines the class of invention and construction cost is outside unevenness. As the roughness of the face increases, the price to improve it also increases thus increasing the rate of the item for consumption. The machine manufacturer will not render the optimum level of spiteful parameter for different materials and it has to be generally found by test and fault method. In direct to attain the maximization of manufacturing dimensions several optimizing techniques were introduced. Some of the past studies are briefed below-

Mondal et al. [1] applied particle swarm process for determining the outside roughness of C40 steel hoist fastener join for centre less grinding operation and estimated most favourable values for insert dimensions viz. deepness of cut, regulating wheel velocity, and coolant gush. Savas et al. [2] had performed optimization of facade bumpiness in a tangential turn milling process on SAE 1050 work piece – HSS tool combination by means of genetic algorithm (GA) . Karabulut et al.[3] determined the outcome of cutting pace, feed velocity, in addition to deepness of scratch on Al7075 and SiC open cell foam compound applying artificial neural networks (ANN). It was estimated that the nourish pace was the on the whole crucial dimension in favour of the entire substances. Routara et al.[4] successfully modelled and optimized various roughness parameters viz. middle line standard unevenness, core mean square unevenness, skewness, kurtosis, and denote row acme spacing for various substances like aluminium, brass, and gentle steel by income of wounding haste, provide for speed, as well as deepness of slash as key dimensions by adopting response surface method (RSM) for optimization. Oktem [5] stated and maximized the cutting dimensions for milling of AISI 1040 steel - TiAlN hard carbide device amalgamation beneath drenched circumstances implementing GA and ANN optimization technique. It was concluded that GA perform healthier than ANN and improved roughness from 0.67 microns to 0.59 microns and machining time got improved from 1.282 minutes to 1.0316 minutes. Kadirgama et al.[6] optimized the input machining parameters viz. cutting pace, feed velocity, axial depth, and symmetric deepness of hack for milling Aluminium alloys (AA 6061-T6) through carbide covered inputs. Probable bear vector appliance was worn to enlarge the predicted model which provided an error of 2-9% when compared with experimental result. Oktem et al.[7] used Taguchi optimization system for face irregularity optimization while milling mould surfaces and estimated that the approach was much suitable; and similar conclusion was provided by Eyup et al.[8]. Bhardwaj et al.[9] introduced Box - Cox makeover with RSM to build up outside unevenness model in conclusion milling of EN 353 steel by means of carbide inputs. Cutting pace, feed, deepness of cut, and snout radius were introduced as the input dimension among which cutting pace was estimated to be the mainly important dimension on outside unevenness. Karkalos et al.[10] examined the downward milling procedure on Ti-6Al-4V ELI Alloy. RSM and ANN approaches were utilized for the reason of optimization and it was concluded that ANN technique was better than RSM technique. Liu et al.[11] investigated slot milling operation on Al 7075 material using precise unkind power spending to develop the face irregularity model. The developed model performed well as compare to the Taguchi model. Bandapalli et al. [12] applied ANN, collective process information organization and compound degeneration scrutiny methods for outside unevenness optimization in soaring pace micro conclusion milling of titanium alloy Ti-6Al-4V. It was concluded that ANN performs better than the other two techniques and provides more accuracy. Zhang et al. [13] examined the Taguchi design function to maximise the exterior quality in milling procedure using L9 orthogonal arrangement. Hamdan et al. [14] examined optimization in high pace manufacturing of stainless steel by taking covered carbide apparatus to realize least amount of cutting forces, and outside unevenness. L9 orthogonal assortment was rendered and an enhancement of 41.3 % was observed. Turgay kivak [15] used Taguchi method for investigation of machining hadfield steel. Out of the three key dimensions viz. cutting tool, speed, and feed rate, feed rate was estimated to be more impacting the outside roughness. Shunmugam et. al [16] used genetic algorithm technique to maximise the manufacturing expenses in face milling for roughing as well as concluding operation. The key dimensions were speediness, supply, and deepness of slash and number of passes whereas the output parameter was the manufacturing expenses. It was observed that the implication of algorithm provided the minimum manufacturing expenses. A multiple regression model was developed by Shunmugam et. al [17] to signify the bond connecting participation and amount produced constraint for multi objective optimisation in wire electro discharge machining.

In the at hand swot up the possessions of manufacturing dimensions during milling of zirconia ceramic material with TiAln covered carbide tool has been investigated. Taguchi L9 orthogonal assortment is been applied for designing the set of parameters and conducting the experiment. ANOVA was applied to discover the most influencing parameter. Linear regression equation was employed to forecast the output value. Finally confirmatory investigations are conceded out for the validation of the technique.

2. INVESTIGATIONAL TECHNIQUE

2.1 Milling Experiment

The milling investigations were conceded out in dehydrated cutting circumstances by means of a CNC HAAS Vf-1 model three-axis CNC milling machine capable of greatest spindle pace of 10000 rpm and a 14.9-kW drive motor. The unit in favour of the milling is made known in Fig. 1. The work piece material used was zirconia ceramic in the structure of a 72 X 42 X 14 mm block as given away in Fig. 2a and 2b and the properties are specified in Table 1. The milling tests were performed at different cutting speeds, feed, and deepness of slash.

Fig. 1. Experimental setup for milling

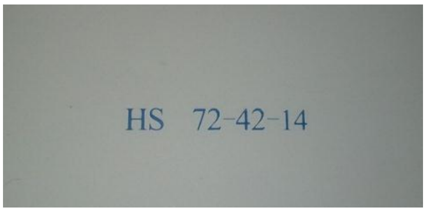

Fig. 2a The illustration of workpiece before machining

Fig. 2b The illustration of effort section after machining

Table 1. Properties of workpiece material

Young Modulus	GPa	200
Hardness	Kg/mm^2	1300
Thermal Conductivity	W/mK	2
Coefficient of Thermal expansion	$10^{-6}/^{0}C$	10
Vickers Hardness	HV	1200

2.2. Cutting tool

The manufacturing investigations utilising flat end TiAln covered carbide tool is shown in Fig. 3. The thickness of the instrument was 3 mm with flank length of 12 mm and helix angle of 300. The hardness of the coating used was 2000 HV with a coating thickness of 5 µm.

Fig. 3. Tool material

2.3. Outside unevenness dimension

The average outside uneveness (Ra) of the effort portion was measured by a Taylor Hobson Talysurf 4 outside unevenness examination. The outside unevenness was measured parallel to the machined surface. Outside unevenness dimension setup is shown in Fig. 4.

Fig. 4. Outside uneveness tester

2.4. Substance taking away pace

The substance elimination pace for machining was estimated by considering into description the proportion of the quantity of substance detached to the time duration essential for machining.

3. EXPERIMENTAL DESIGN

The Taguchi orthogonal assortment has been applied by various researchers in various fields of application as it provides reduction in several investigations or tests to be performed for the purpose of choosing the optimum parameters. The Taguchi process applies a failure purpose to estimate the divergence amid the investigational values and the preferred values. This loss function was again changed into a signal to noise (S/N) proportion. About three kinds of quality aspects in the scrutiny along with examination of S/N ratio is used, that are below the finer, advanced the finer, and nominal the finest [15]. For every stage of the procedure parameters, the S/N proportion was calculated based on the S/N analysis. The reason of the put into effect was to decrease outside unevenness and make the most of the substance elimination pace.

Therefore below the finer and advanced the finer feature equation was used as made known in Eq. 1 and 2.

$$\text{Below the finer aspect } \frac{S}{N} = -10log\frac{1}{n}(\sum x^2) \tag{1}$$

$$\text{Advanced the finer aspect } \frac{S}{N} = -log\frac{1}{n}(\sum \frac{1}{x^2}) \tag{2}$$

Where x is the production variable and 'n' is the quantity of interpretation

Cutting momentum, feed rate, and intensity of cut were chosen as the restrictive features at diverse levels as revealed in Table 2. For three participation dimensions at three diverse levels L9 orthogonal assortment has been applied by various researchers and hence, the same has been applied in this learning.[18]–[21]. The L9 orthogonal selection is made known in Table 3. The careful feedbacks and the signal to noise ratios estimated applying equation no. 1 and 2 are also revealed.

Table 2. Milling dimensions and their stages

Parameters	Units	Level1	Level2	Level3
Cutting momentum (A)	rpm	7500	8500	9500
Feed rate (B)	mm/min	75	105	135
Intensity of cut (C)	mm	0.4	0.8	1.2

Table 3. L9 Orthogonal assortment with the measured responses and S/N ratio

Experiment No.	Factor			Ra (µm)	S/N Ratio	MRR (mm^3/min)	S/N Ratio
	(A)	(B)	(C)				
1	7500	75	0.4	0.497	6.073	31.746	30.034
2	7500	105	0.8	0.390	8.179	73.394	37.313
3	7500	135	1.2	0.341	9.345	240.00	47.604
4	8500	75	0.8	0.263	11.601	64.00	36.124
5	8500	105	1.2	0.317	9.979	115.385	41.243
6	8500	135	0.4	0.358	8.922	78.431	37.890
7	9500	75	1.2	0.260	11.701	95.238	39.576
8	9500	105	0.4	0.261	11.667	39.216	31.869
9	9500	135	0.8	0.311	10.145	156.863	43.910

4. ANALYSIS OF EXPERIMENTS

4.1 ANOVA

Analysis of variance (ANOVA) is a method which has been usually applied by numerous authors [13], [18], [19],[22],[23] for finding the entity implications of the control features on the output response. ANOVA is also introduced to inspect the investigational facts and figures. In the current learning, the ANOVA was performed for outside unevenness as shown in Table 4 for 95 % confidence level to assess the contribution of various factors. The F value = 2.48 of cutting momentum establishes it as the majority noteworthy feature (59.62%). The impact of A, B and C features on the outside unevenness were observed to be 59.62%, 1.08% and 15.23% correspondingly.

The ANOVA for substance elimination pace is exposed in Table 5. The highest contribution in percentage is inferred by feed rate (PC=46.97%), followed by intensity of cut (44.61 %), and lastly by cutting momentum (3.81 %).

Table 4. Anova Table for outside unevenness

Starting place	DF	Adj SS	Adj MS	F value	Contribution (%)
Cutting momentum	2	0.028017	0.014008	2.48	59.62
Feed rate	2	0.000508	0.000254	0.04	1.08
Intensity of cut	2	0.007158	0.003579	0.63	15.23
Error	2	0.011304	0.005652		24.07
Total	8	0.046987			

Table 5. Anova Table for substance elimination pace

Starting place	DF	Adj SS	Adj MS	F value	Contribution (%)
Cutting momentum	2	1294	646.9	0.83	3.81
Feed rate	2	15929	7964.4	10.22	46.97
Intensity of cut	2	15131	7565.3	9.71	44.61
Error	2	1558	779.1		4.61
Total	8	33911			

4.2 S/N Ratio

The result of input dimensions was estimated on the outside unevenness and substance elimination pace applying S/N feedback table. The feedback counter for S/N proportion for outside unevenness along with substance elimination pace employing Taguchi method is made known in Table 6. It also shows the optimal values (bold) of the various dimensions for least amount of outside unevenness and utmost substance elimination pace which is also shown in Fig.5 and Fig. 6. According to the S/N proportion the factors giving optimum outside unevenness values were specified as factor A (Level 3, S/N=11.171), factor B (Level 2, S/N=9.942), and factor C (Level 3, S/N=10.341). Optimum outside unevenness value was obtained with a momentum of 9500 rpm (A3) at feed rate of 105 mm/s (B2) with an intensity of cut for 1.2 mm (C3). Mean effect of the procedure dimensions on the denote response were also analyzed. The mean response is referred to the average worth of the counter for every aspect at different levels. Hence the middling value of outside unevenness for every feature at three levels was estimated and outlined as revealed in Fig. 7. The graph indicates the optimum level of parameters which is similar to what is gained in S/N ratio analysis. Likewise levels and S/N proportions for the features rendering the most favourable substance elimination pace were rendered as factor A (Level 3, S/N=38.45), factor B (Level 3, S/N=43.13), and factor C (Level 3, S/N=42.81). Optimum substance elimination pace value was obtained with a momentum of 9500 rpm (A3) at feed rate of 135 mm/s (B3) with an intensity of cut for 1.2 mm (C3). The graph for mean effects for substance elimination pace is made known in Fig.8

Table 6. Optimum Values

S/N answer counters for outside unevenness

Levels	Control Factors		
	A	B	C
Level 1	7.865	9.791	8.887
Level 2	10.167	**9.942**	9.975
Level 3	**11.171**	9.471	**10.341**
Delta	3.305	0.471	1.454
Rank	1	3	2

Bold values shows optimum levels

S/N answer counters for substance elimination pace

Levels	Control Factors		
	A	B	C
Level 1	38.32	35.24	33.26
Level 2	38.42	36.81	39.12
Level 3	**38.45**	**43.13**	**42.81**
Delta	0.13	7.89	9.54
Rank	3	2	1

Bold values shows optimum levels

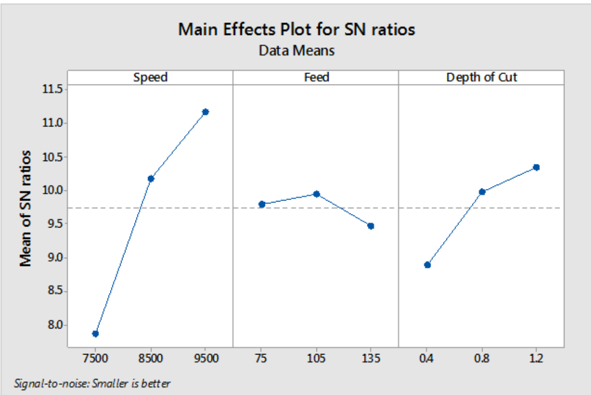

Fig. 5. Major influential plan for SN proportions on outside unevenness

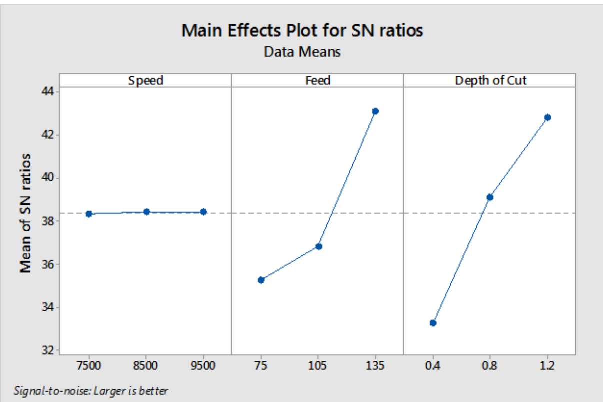

Fig. 6. Major influential plan for SN proportions on substance elimination pace

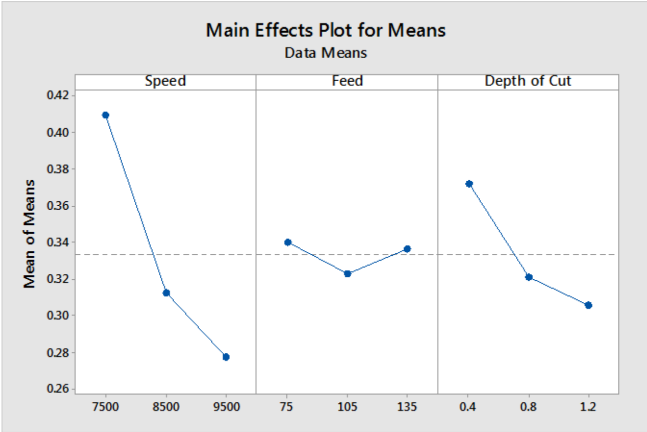

Fig.7. Major influential plan for means on outside unevenness

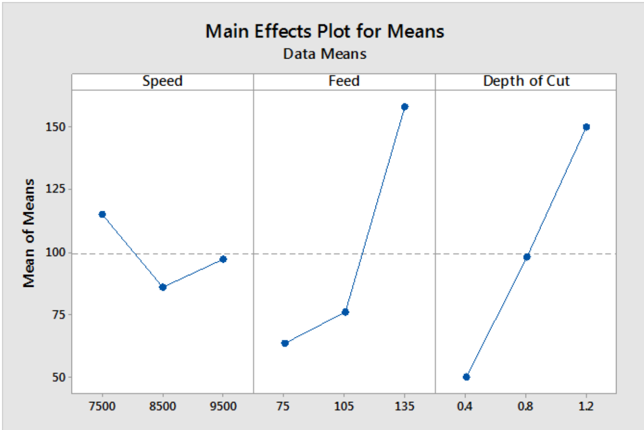

Fig. 8 Major influential plan for means on substance elimination pace

It is capable of the estimation from Fig. 6 that as the cutting momentum rises the contact amid the instrument along with the effort substance lessens, the chip fracture lessens and thus, the unevenness lessens that renders a result given by Palanikumar et. al.[24]. An enhance in feed rate results in reduction of unevenness up to some extent. However, with additional increase in feed rate the unevenness rises. It may be renowned that enhance in the intensity of cut results in more area being exposed to the cutter for machining which improves the unevenness of the effort material. This can observed by Fig. 8 that as the momentum, feed rate and intensity of cut increases the substance elimination pace also increases because it exposes more area to the cutter in less amount of time, which is with reference to Taylor et.al.[25].

4.3 Regression analysis

Regression analysis is defined as a array of statistical procedures which is applied for rendering co- relationships between the variables. It is applied to frame a co-relation amid reliant and self-governing variables. As per the examination it was established that outside unevenness and substance elimination pace are reliant variables whereas cutting momentum, feed rate, and intensity of cut are self-governing variables. The equations formed between the variables by the least square linear regression model are given below Eq. 3 for outside unevenness in addition to Eq. 4 for substance elimination pace.

OU = 0.966 - 0.000066 cutting momentum - 0.000056 feed rate - 0.0825 intensity of cut (3)

SEP = -91 - 0.0090 cutting momentum + 1.579 feed rate + 125.5 intensity of cut (4)

5. VALIDATION OF OPTIMUM PARAMETERS

In charge to get hold of the maximization output the machine needs to work upon the parameters which will favour it. Hence, the parameters favouring optimum OU along with SEP obtained from Table 6 are specified in Table 7. The best possible standards of OU along with SEP obtained from Eq. 3 and 4 are specified in the table below. Actual experiments were then conducted taking the optimum values as the input parameters. Average results of three experiments were noted and value for OU was found to be 0.25 as compared to 0.234 obtained from Eq 3. Similarly for SEP predicted value using Eq.4 was established to be 187.98 as match to the actual value of 196.72.

The differences between definite along with forecasted values are made known in Table 7. The difference in the values of definite along with forecasted OU is 11.36 % whereas for SEP it is 4.44 %. It is to be able to be seen that the proportion of error is less than 12 % for obtaining optimum values for manufacturing of zirconia ceramic material using Tungsten Carbide tool. Hence it is able to be concluded that Taguchi orthogonal array, S/N ratio and regression equation be able to be applied for obtaining the best possible dimensions for machining.

Table 7. Predicted and Experiment values for optimum conditions

Response	Factor A	B	C	Output Predicted Regression	Experiment value	Error %
Ra	9500	105	1.2	0.234	0.264	11.36
MRR	9500	135	1.2	187.98	196.72	4.44

6. CONCLUSION

In this learning, taguchi technique and regression examination was applied to maximise outside unevenness and substance elimination pace for milling of zirconia ceramic material using TiAln tool. The investigational outcomes were examined applying Minitab 17 application and the subsequent resultants can be observed.

Taguchi technique plus regression examination was found very effective in optimizing the OU and SEP with very less difference between forecasted with definite values.

- The best possible stage of parameters for optimum OU was established to be 9500 rpm as cutting momentum, 105 mm/min as feed rate, and 1.2 mm as intensity of cut.
- The best possible stage of parameters for optimum SEP was established to be 9500 rpm as cutting momentum, 135 mm/min as feed rate, and 1.2 mm as intensity of cut.
- For outside unevenness the cutting momentum was measured to be the foremost prevailing feature (59.62%) while for substance removal pace the foremost prevailing feature was feed rate (46.97%) and consequently intensity of cut (44.61%).

The entire the over specified points ultimately reach to a conclusion that taguchi technique and regression analysis can be efficiently worn for the maximization of feedbacks that decreases the indict of operating investigational activity. Further studies can be conduct by means of this technique with different factors or tool materials to explore the effects of such factors on OU along with SEP.

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